Internet Appendix for

The Impact of Hedge Funds on Asset Markets

This internet appendix provides supplemental analyses to "The Impact of Hedge Funds on Asset Market".

The first section describes a Monte Carlo simulation to study the finite-sample size of our extension of Clark and West (2006). The second section presents a stylized model to study how hedge fund style "drift" or style misreporting can affect the informativeness of an illiquidity index based on funds from a single style category relative to an aggregate index based on all hedge funds. The third section presents the proof of the differentiability of the hedge fund utility function at the jump of the indicator function. The fourth section contains three figures showing the difference of cumulative squared errors between the baseline model and our single variable model with the hedge fund illiuqidity index as predictor. In the last section, we present a table with detailed results for predictive in-sample regressions for US corporate bonds. The tables and figures are as follows:

A Monte Carlo Simulation Study

To study the finite-sample size of this extension of Clark and West (2006) we conduct a small simulation study. The target variable and forecasts are generated as follows:

$$
\begin{aligned}
Y_t &= \gamma^* + \beta^* \bar{X}_t + \varepsilon_t, \qquad \text{(IA.1)} \\
\text{where } \bar{X}_t &\equiv \frac{1}{k}\sum_{i=1}^{k} X_{it} \\
\left[X_t', \varepsilon_t\right]' &\sim iid\ N\left(0, \mathbf{I}_{k+1}\right) \\
\hat{Y}_{t+1|t}^{(1)} &= \hat{\gamma}_t \\
\hat{Y}_{t+1|t}^{(2)} &= \left[1, X_{t+1}'\right]\hat{\beta}_t
\end{aligned}
$$

To study the finite-sample size properties of the test, we set $\beta^* = 0$, and so the DGP includes just a consant, γ^*. In this case both models are correct, but Forecast 1 will do better in finite samples because it does not include any irrelevant variables. To study power we let $\beta^* = 0.1$, which means that each of the included regressors in Forecast 2 is useful, and Forecast 1 is misspecified.

We consider in-sample estimation period lengths of $R \in \{100, 200, 500, 1000, 5000\}$, and an out-of-sample evaluation period of $P = 1000$. The number of extra regressors in the larger model is set to $k \in \{1, 5, 10\}$. We repeat the simulation 1000 times.

In Table IA.I we present the finite-sample rejection probabilities when the null hypothesis is true, using 0.05 level tests. We report our proposed "adjusted" test, as well as the usual "unadjusted" test, which corresponds to the Diebold and Mariano (1995) test. Table IA.I shows that the unadjusted test is very conservative (with rejection probabilities much lower than 0.05), particularly for small R. The "adjusted" test provides better size control, with rejection probabilities closer to the nominal 0.05 level. The improvement from the adjustment is particularly great when k is large and R is small, consistent with theory.

Table IA.II reports rejection probabilities when the null is false, which provides insights into the power of the adjusted and unadjusted tests. Consistent with the results under the null, the unadjusted test has low power to reject the null when it is false, and we see that the adjusted test has much better power than the unadjusted test. Figure IA.I illustrates where the gains come from: the adjusted test re-centers the distribution of test statistics on zero, which makes the test less conservative under the null, and more powerful under the alternative.

Tabel AI.I: Rejection Probabilities When Null Hypothesis Is True

This table presents the rejection probabilities from the "unadjusted" and "adjusted" tests of equal predictive accuracy, at the 0.05 level. R represents the length of the in-sample estimation period; k represents the number of regressors in the larger model (excluding the constant).

	R=100	R=200	R=500	R=1000	R=5000
			k=1		
Unadjusted	0.000	0.000	0.001	0.002	0.013
Adjusted	0.030	0.027	0.031	0.019	0.031
			k=5		
Unadjusted	0.000	0.000	0.000	0.000	0.013
Adjusted	0.049	0.035	0.042	0.050	0.049
			k=10		
Unadjusted	0.000	0.000	0.000	0.000	0.009
Adjusted	0.057	0.042	0.047	0.046	0.043

Tabel AI.II: Rejection Probabilities When Null Hypothesis Is False

This table presents the rejection probabilities from the "unadjusted" and "adjusted" tests of equal predictive accuracy, at the 0.05 level. R represents the length of the in-sample estimation period; k represents the number of regressors in the larger model (excluding the constant).

	R=100	R=200	R=500	R=1000	R=5000
			k=1		
Unadjusted	0.014	0.079	0.249	0.382	0.450
Adjusted	0.631	0.741	0.846	0.906	0.923
			k=5		
Unadjusted	0.014	0.364	0.869	0.949	0.962
Adjusted	0.997	1.000	1.000	1.000	1.000
			k=10		
Unadjusted	0.004	0.599	0.996	0.998	1.000
Adjusted	1.000	1.000	1.000	1.000	1.000

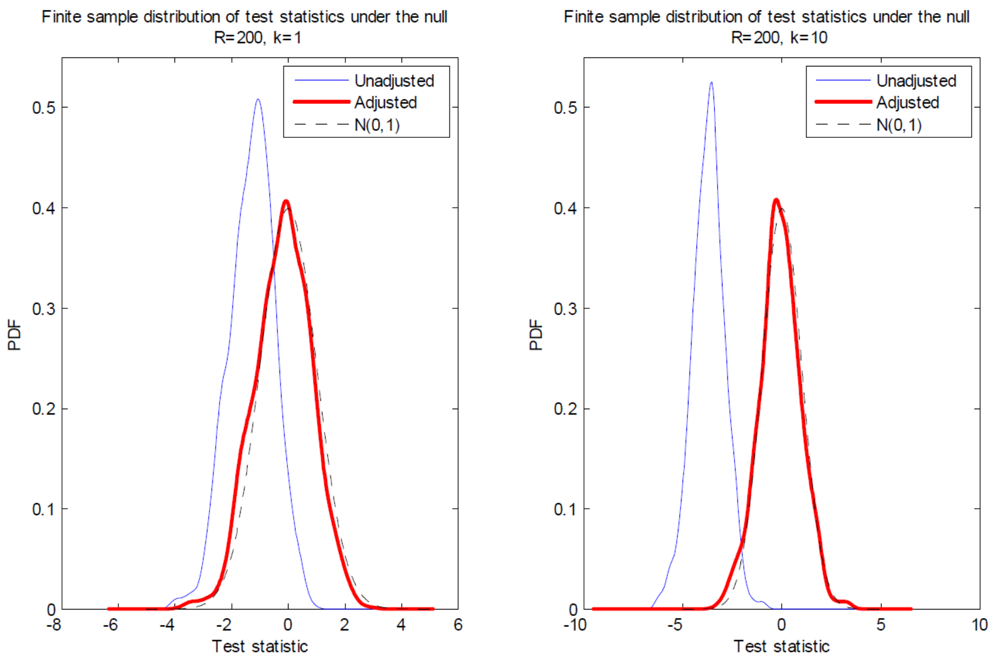

Figure IA.I: Distribution of the test statistics from the "unadjusted" and "adjusted" tests across 1000 simlations. The in-sample period length is 200 and the out-of-sample length is 1000 observations. The larger model includes a single extra regressor (left panel) or 10 extra regressors (right panel).

Hedge Fund Style Indices vs. an Aggregate Index

This appendix presents a stylized model to study how hedge fund style "drift" or style misreporting can affect the informativeness of an illiquidity index based on funds from a single style category relative to an aggregate index based on all hedge funds.

Consider the following simple framework. There are N individual hedge funds (with N large; in our empirical application it is 29,496). There are $S = 10$ different styles (to match our empirical application), and we will assume that there are $K = N/S$ funds in each style.

Assume that for each hedge fund style there is an asset index that is "close" to that style, so there are also S asset indices. (e.g., Fixed income hedge funds and corporate bond returns, security selection hedge funds and equity returns, etc.) Returns on each asset class index are linked to liquidity, and have a component that is not related to liquidity:

$$r_{s,t+1} = \alpha_s^* + \beta_s^* L_{s,t}^* + u_{s,t+1}^*, \quad s = 1, 2, ..., S \tag{IA.2}$$

We will assume that all parameters are the same across styles, all shocks are mean zero, Normal, homoskedastic, and independent from each other.

Hedge fund returns for funds in a given style provide us with a noisy estimate of the liquidity of that asset class:

$$\begin{aligned} \tilde{L}_{i,t} &= L_{s(i),t}^* + \eta_{i,t}, \text{ for } i = 1, 2, .., N \\ \text{where } s(i) &\in \{1, 2, ..., S\} \end{aligned} \tag{IA.3}$$

$s(i)$ is the style of hedge fund i. (In our application our noisy estimate of hedge fund liquidity is based on autocorrelations; we abstract from that particular measure here and simply consider a generic noisy measure of liquidity.) We average the liquidity estimates from each fund in style s to obtain an aggregate liquidity index for that style:

$$\bar{L}_{s,t} = \frac{1}{K} \sum_{i=1}^{N} \tilde{L}_{i,t} \mathbf{1}\{s(i) = s\} \tag{IA.4}$$

and across all funds to get an aggregate liquidity index:

$$\bar{L}_t = \frac{1}{N} \sum_{i=1}^{N} \tilde{L}_{i,t} \tag{IA.5}$$

We use the (noisy) liquidity indices extraced from hedge fund returns in a regression to try to predict future asset index returns:

$$r_{s,t+1} = \tilde{\alpha}_s + \tilde{\beta}_s \bar{L}_{s,t} + \tilde{u}_{s,t+1}, \quad s = 1, 2, ..., S \tag{IA.6}$$

Clearly, the closer $\bar{L}_{s,t}$ is to $L^*_{s,t}$, the better this prediction will be.

Case 1: Styles are correctly reported

In this baseline case

$$\begin{aligned} \bar{L}_{s,t} &= \frac{1}{K} \sum_{i=1}^{N} \left(L^*_{s,t} + \eta_{i,t} \right) \mathbf{1} \left\{ s(i) = s \right\} \\ &= L^*_{s,t} + \frac{1}{K} \sum_{i=1}^{N} \eta_{i,t} \mathbf{1} \left\{ s(i) = s \right\} \\ &\equiv L^*_{s,t} + \epsilon_{s,t}, \qquad \epsilon_{s,t} \sim N \left(0, \frac{1}{K} \sigma^2_\eta \right) \end{aligned} \tag{IA.7}$$

The estimated coefficient on $\bar{L}_{s,t}$ is:

$$\tilde{\beta}_s = \frac{Cov \left[\bar{L}_{s,t}, r_{s,t+1} \right]}{V \left[\bar{L}_{s,t} \right]} = \frac{Cov \left[L^*_{s,t} + \epsilon_{s,t}, r_{s,t+1} \right]}{V \left[L^*_{s,t} + \epsilon_{s,t} \right]} = \beta^*_s \frac{1}{1 + \sigma^2_\eta / \left(K \sigma^2_L \right)} \tag{IA.8}$$

where $\sigma^2_L = V \left[L^*_{s,t} \right]$. This is the familiar shrinkage of a regression parameter towards zero when the dependent variable is measured with error. The R^2 of this model is

$$\tilde{R}^2 = Corr \left[\bar{L}_{s,t}, r_{s,t+1} \right]^2 = \frac{Cov \left[L^*_{s,t}, r_{s,t+1} \right]^2}{\left(\sigma^2_L + \frac{1}{K} \sigma^2_\eta \right) \sigma^2_r} = R^{*2} \frac{1}{1 + \sigma^2_\eta / \left(K \sigma^2_L \sigma^2_r \right)} \tag{IA.9}$$

where R^{*2} is the R^2 from the regression if we could directly observe $L^*_{s,t}$, and $\sigma^2_r = V \left[r_{s,t+1} \right]$. Next, we compare the above base case with what is obtained in the presence of style mis-labelling, style drift, etc.

Case 2: Style "mis-labelling"

Perhaps because of style drift, or style mis-reporting, or just errors in classifying the hedge fund style, it may be that a fund that is listed as being in style s is actually in style j. Let p be the probability that the reported style label, denoted $\tilde{s}(i)$, is correct, i.e.,

$$p = \Pr \left[\tilde{s}(i) = s(i) \right] \tag{IA.10}$$

and assume this is the same across funds. For simplicity, assume that when the label is *incorrect*, the label is randomly chosen from the remaining $S - 1$ styles.

To obtain the main results for this case, we will use the fact that

$$\begin{aligned} \frac{1}{N}\sum_{i=1}^{N}\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=s\right\} &\approx E\left[\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=s\right\}\right] \quad \text{for } N \text{ large} \\ &= \Pr\left[\tilde{s}\left(i\right)=s,s\left(i\right)=s\right] \\ &= \Pr\left[\tilde{s}\left(i\right)=s|s\left(i\right)=s\right]\Pr\left[s\left(i\right)=s\right] \\ &= p\frac{1}{S} \end{aligned} \tag{IA.11}$$

and

$$\begin{aligned} \frac{1}{N}\sum_{i=1}^{N}\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=j\neq s\right\} &\approx E\left[\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=j\neq s\right\}\right] \\ &= \Pr\left[\tilde{s}\left(i\right)=s,s\left(i\right)=j\neq s\right] \\ &= \Pr\left[\tilde{s}\left(i\right)=s|s\left(i\right)=j\neq s\right]\Pr\left[s\left(i\right)=j\neq s\right] \\ &= \frac{1-p}{S-1}\frac{1}{S} \end{aligned} \tag{IA.12}$$

So we can obtain:

$$\begin{aligned} \bar{L}_{s,t} &= \frac{1}{K}\sum_{i=1}^{N}\left(L^*_{s(i),t}+\eta_{i,t}\right)\mathbf{1}\left\{\tilde{s}\left(i\right)=s\right\} \\ &= \sum_{j=1}^{S}L^*_{j,t}\frac{1}{K}\sum_{i=1}^{N}\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=j\right\}+\underbrace{\frac{1}{K}\sum_{i=1}^{N}\eta_{i,t}\mathbf{1}\left\{\tilde{s}\left(i\right)=s\right\}}_{\equiv\epsilon_{s,t}\sim N\left(0,\sigma^2_\eta/K\right)} \\ &= L^*_{s,t}\frac{1}{K}\sum_{i=1}^{N}\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=s\right\}+\sum_{j=1,j\neq s}^{S}L^*_{j,t}\frac{1}{K}\sum_{i=1}^{N}\mathbf{1}\left\{\tilde{s}\left(i\right)=s,s\left(i\right)=j\right\}+\epsilon_{s,t} \\ &= L^*_{s,t}\frac{N}{K}\frac{p}{S}+\sum_{j=1,j\neq s}^{S}L^*_{j,t}\frac{N}{K}\frac{1-p}{S-1}\frac{1}{S}+\epsilon_{s,t} \\ &= pL^*_{s,t}+\frac{1-p}{S-1}\sum_{j=1,j\neq s}^{S}L^*_{j,t}+\epsilon_{s,t} \end{aligned} \tag{IA.13}$$

using the fact that $N/K=S$. This last line expresses $\bar{L}_{s,t}$ as a weighted average of each of the individual style indices. We can re-write it to be a weighted average of just the target style index and the "All" index:

$$\begin{aligned}\bar{L}_{s,t} &= pL^*_{s,t} + \frac{1-p}{S-1}\sum_{j=1,j\neq s}^{S} L^*_{j,t} + \epsilon_{s,t} \\ &= pL^*_{s,t} + \frac{1-p}{S-1}\sum_{j=1}^{S} L^*_{j,t} + \epsilon_{s,t} - \frac{1-p}{S-1}L^*_{s,t} \\ &= \frac{pS-1}{S-1}L^*_{s,t} + \frac{1-p}{S-1}\sum_{j=1}^{S} L^*_{j,t} + \epsilon_{s,t} \\ &= \frac{pS-1}{S-1}L^*_{s,t} + \frac{S(1-p)}{S-1}\bar{L}^*_t + \epsilon_{s,t}\end{aligned} \tag{IA.14}$$

Note that the noise term, $\epsilon_{s,t}$, does not depend on p, but it *does* depend on K through its variance. When $p = 1$ the style label is always correct and we obtain:

$$\bar{L}_{s,t} = L^*_{s,t} + \epsilon_{s,t} \tag{IA.15}$$

as in the base case. When $p = 1/S$ the style label is correct as often as a random guess and we obtain

$$\bar{L}_{s,t} = \frac{\frac{1}{S}S-1}{S-1}L^*_{s,t} + \frac{S\left(1-\frac{1}{S}\right)}{S-1}\bar{L}^*_t + \epsilon_{s,t} = \bar{L}^*_t + \epsilon_{s,t} \tag{IA.16}$$

That is, when the labels are randomly applied, the index average is equal to the aggregate index average plus some measurement error.

The above calculations reveal the "bias-variance" trade-off between using a style-specific index and using an aggregate index: When we average across all funds we get an index centered on the average liquidity, $\bar{L}^*_t$, which is not really what we want (a form of bias), but it has small measurement error (lower variance): $\epsilon_t \sim N\left(0, \sigma^2_\eta/N\right)$. When we average across just those funds in the style we care about we get an index that is more heavily weighted on the style we care about (for values of $p > 1/S$), but it has greater measurement error: $\epsilon_{s,t} \sim N\left(0, \sigma^2_\eta/K\right)$.

To find the "threshold" value for p that makes these two approaches equally accurate, we need to take a stand on the correlation between liquidity factors in different styles. To generate correlation between liquidity in different asset classes, we assume a simple factor structure. Let:

$$L^*_{s,t} = \gamma L^*_{c,t} + \nu_{s,t}, \quad s = 1, 2, ..., L \tag{IA.17}$$

Without loss of generality, let $V\left[L^*_{c,t}\right] = 1$, and then note that $\sigma^2_\nu = \sigma^2_L - \gamma^2$. Note that the R^2 of this regression is:

$$\rho^2_c \equiv Corr\left[L^*_{s,t}, L^*_{c,t}\right]^2 = \frac{\gamma^2}{\gamma^2 + \sigma^2_v} = \frac{\gamma^2}{\sigma^2_L} \tag{IA.18}$$

Then we obtain:

$$
\begin{aligned}
Cov\left[L^*_{s,t}, L^*_{j,t}\right] &= \gamma^2 \qquad \text{(IA.19)}\\
\text{and} \quad Cov\left[r_{s,t+1}, L^*_{s,t}\right] &= \beta^* \sigma^2_L \\
Cov\left[r_{s,t+1}, L^*_{j,t} | j \neq s\right] &= Cov\left[r_{s,t+1}, \gamma L^*_{c,t} + \nu_{j,t}\right] \\
&= Cov\left[r_{s,t+1}, \gamma\left(\gamma \frac{1}{\sigma^2_L} L^*_{s,t} + z_t\right) + \nu_{j,t}\right] \\
&= \gamma^2 \frac{1}{\sigma^2_L} Cov\left[r_{s,t+1}, L^*_{s,t}\right] \\
&= \rho^2_c \beta^* \sigma^2_L
\end{aligned}
$$

So if the common component is very strong (ρ_c is near ± 1) then using the "wrong" style liquidity does not matter; it is almost as good as the right style. When the common component is weak, the covariance is pulled towards zero.

Now consider the R^2 from the predictive regression using the aggregate index. First we obtain the covariance between the aggregate index and a given asset style return:

$$
Cov\left[\bar{L}_t, r_{s,t+1}\right] = \frac{1}{S} Cov\left[L^*_{s,t}, r_{s,t+1}\right] + \frac{1}{S} \sum_{j=1, j\neq s}^{S} Cov\left[L^*_{j,t}, r_{s,t+1}\right] \qquad \text{(IA.20)}
$$

$$
= \frac{1 + (S-1)\rho^2_c}{S} \beta^* \sigma^2_L
$$

and the variance of the aggregate index:

$$
\begin{aligned}
V\left[\bar{L}_t\right] &= \frac{1}{S^2} V\left[\sum_{j=1}^{S} L_{j,t}\right] + V\left[\epsilon_t\right] = \frac{1}{S^2} V\left[S\gamma L^*_{c,t}\right] + \frac{1}{S^2}\sum_{j=1}^{S} V\left[\nu_{j,t}\right] + \frac{1}{N}\sigma^2_\eta \qquad \text{(IA.21)}\\
&= \frac{(S-1)K\gamma^2 + K\sigma^2_L + \sigma^2_\eta}{N} \\
&= \frac{(S-1)}{S}\gamma^2 + \frac{1}{S}\sigma^2_L + \frac{1}{N}\sigma^2_\eta
\end{aligned}
$$

Combing the above we find that the R^2 is

$$
\begin{aligned}
R^2_{all} &= \frac{\left(1 + (S-1)\rho^2_c\right)^2 K \beta^{*2} \sigma^4_L}{(S-1) N \rho^2_c \sigma^2_L + N\sigma^2_L + S\sigma^2_\eta} \frac{1}{\sigma^2_r} \qquad \text{(IA.22)}\\
&= \left(1 + (S-1)\rho^2_c\right)^2 \frac{K}{S} \frac{1}{\left((S-1)K\rho^2_c + K + \lambda^2\right)} R^{*2},
\end{aligned}
$$

where $\lambda^2 \equiv \frac{\sigma^2_\eta}{\sigma^2_L}$ and $R^{*2} \equiv Corr\left[L^*_{s,t}, r_{s,t+1}\right]^2 = \frac{\beta^{*2}\sigma^2_L}{\sigma^2_r}$.

We can contrast this R^2 with that obtained from the individual style liquidity index:

$$R_s^2 = \frac{p^2 (S-1) K}{(p^2 S - 2p + 1) K + (S-1) \lambda^2} R_s^{*2} \tag{IA.23}$$

Using these two expressions, we can solve for the value p^* that equates them. The solution is lengthy and we illustrate it below. The comparative statics reveal that the required proportion of correct individual style labels (p^*) is higher when:

1. Holding the number of individual funds (N) fixed, the number of hedge funds in each style (K) is lower or the number of styles (S) is higher: fewer funds per style means the individual style index is noisier.

2. The noise to signal ratio of each individual liquidity estimate ($\lambda \equiv \sigma_\eta / \sigma_L$) is higher.

3. The correlation between the individual style liquidity measures and the common liquidity measure (ρ_c) is higher: when this is higher the aggregate index does better, and so the style labels must be accurate with higher probability to counteract this.

In our data, the average correlation between our style indices is $\rho_L = 0.5869$, suggesting that $\rho_c = 0.7661$. This approximately corresponds to the thick solid line in Figure IA.II below.

In summary, Figure AI.II reveals that depending on the parameters that describe the model, it is possible that the individual style illiquidity index is always preferred, is never preferred, or is sometimes preferred to the aggregate index. Thus, which illiquidity index to use in practice is something that needs to be determined empirically.

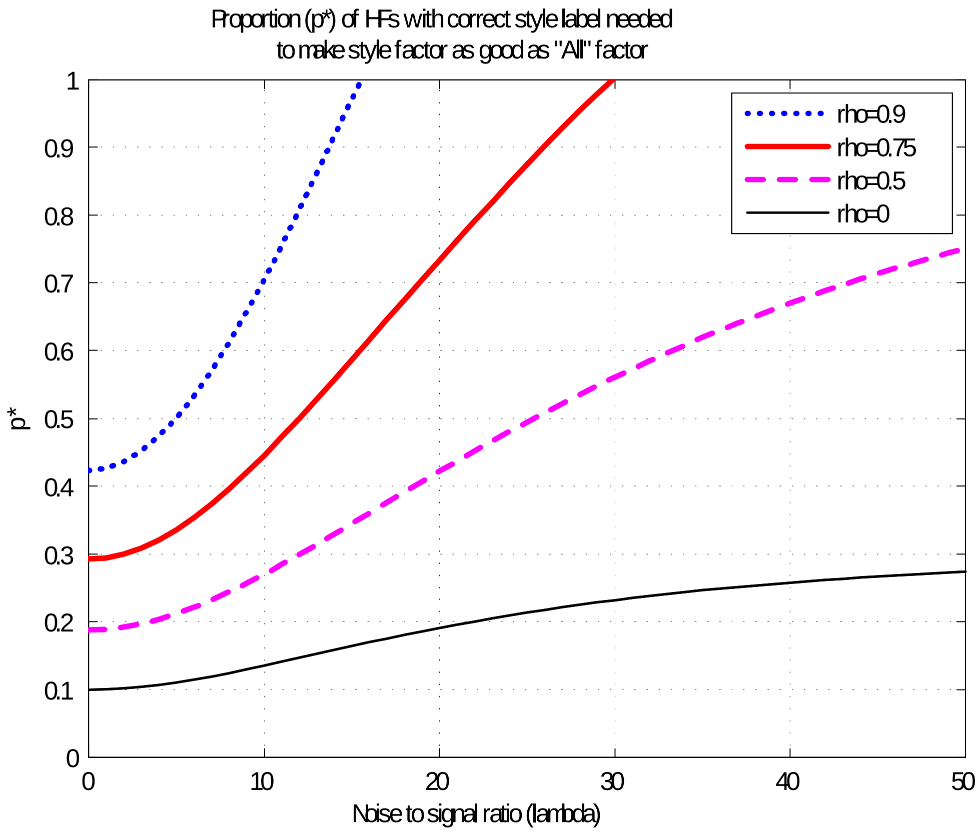

Figure IA.II: Proportion of hedge funds with the correct style label needed to make the style liquidity index as good as the aggregate liquidity index. The x-axis shows the noise-to-signal ratio of individual liquidity measures, and the four lines consider differing degrees of correlation between liquidity across styles.

Differentiability of Hedge Fund Utiliy Function at Jump of Indicator Function

The objective function is

$$Q(x_1) = x_1(E[d_2] - p_1) - \frac{\alpha}{2}x_1^2\sigma^2 - \frac{\lambda}{2}(\Phi_{max} - C_0 + x_1p_1)^2 I\{\Phi_{max} \geq C_0 - x_1p_1\}. \qquad \text{(IA.24)}$$

We want to prove that the derivative Q' exists at $x_{1,0} \equiv \frac{\Phi_{max}-C_0}{-p_1}$.

By definition, the derivative $Q'(x_{1,0})$, if it exists, is the limit of

$$\frac{Q(x_{1,0}+h) - Q(x_{1,0})}{h} \qquad \text{(IA.25)}$$

as $h \to 0$. Substituting in the objective function given in equation (IA.24) and simplifying yields

$$\frac{h(E[d_2] - p_1) - \frac{\alpha}{2}(2hx_{1,0} + h^2)\sigma^2 - \lambda\frac{1}{2}(hp_1)^2 I\{\Phi_{max} \geq C_0 - (x_{1,0}+h)p_1\}}{h}. \qquad \text{(IA.26)}$$

The h in the denominator cancels out:

$$(E[d_2] - p_1) - \frac{\alpha}{2}(2x_{1,0} + h)\sigma^2 - \lambda\frac{1}{2}hp_1^2 I\{\Phi_{max} \geq C_0 - (x_{1,0}+h)p_1\}. \qquad \text{(IA.27)}$$

The limit as $h \to 0$ of the first two term in equation (IA.28) are clearly $E[d_2] - p_1$ and $\alpha x_{1,0}\sigma^2$. The limits of the third term from the *right* and from the *left* are

$$\begin{aligned} \lim_{h\to 0^+} \lambda\frac{1}{2}hp_1^2 \times I\{\Phi_{max} \geq C_0 - (x_{1,0}+h)p_1\} &= L^+ = 0 \times 1 = 0, \\ \lim_{h\to 0^-} \lambda\frac{1}{2}hp_1^2 \times I\{\Phi_{max} \geq C_0 - (x_{1,0}+h)p_1\} &= L^- = 0 \times 0 = 0. \end{aligned} \qquad \text{(IA.28)}$$

Since $L^+ = L^-$ the limit exists, and is zero. Hence, $Q'(x_{1,0}) = (E[d_2] - p_1) - \alpha x_{1,0}\sigma^2$. Note that the second derivative of $Q(x_1)$ does not exist at $x_{1,0}$. However, since the mean-variance preferences are concave and the shortfall penalty is less than zero, it can be shown that $x_{1,0}$ is a maximum conditional on satisfying the first order condition without checking the second order condition.

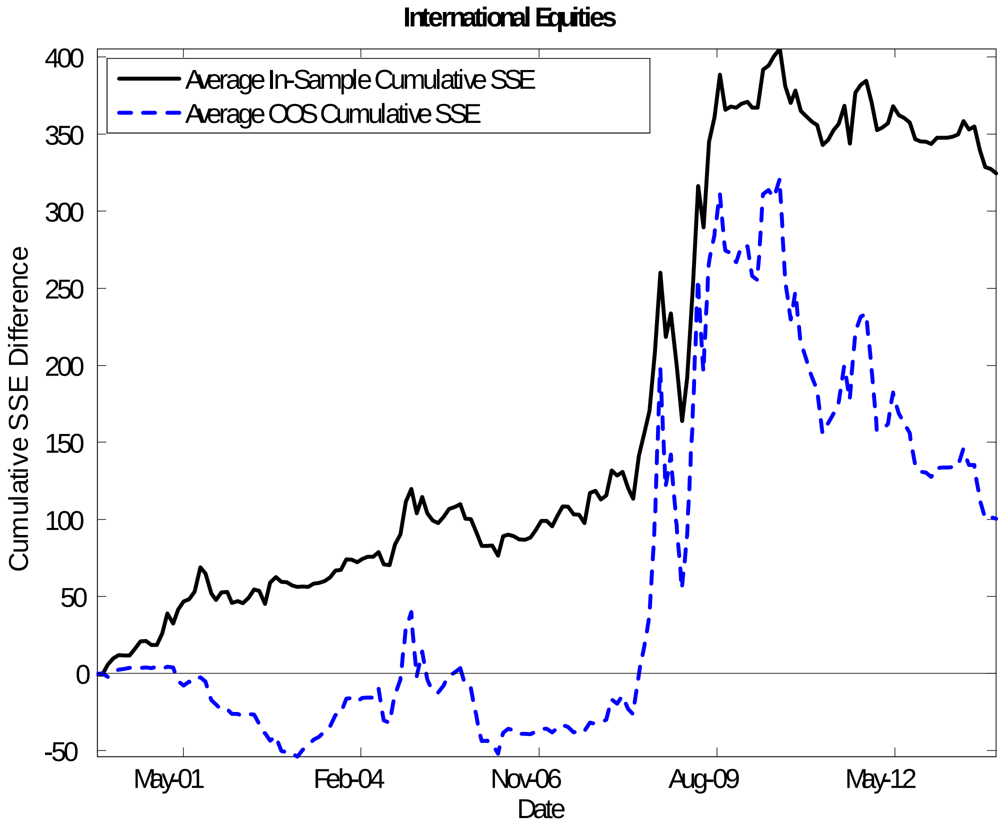

Figure IA.III: The OOS line shows the difference of the cumulative OOS squared forecasting errors of the historical average model and the single variable model with the equally weighted hedge fund illiquidity index as predictor. Five year rolling windows are used. The in-sample line shows the difference of the cumulative sum of squared residuals of a model with just a constant and the residuals of a single variable model with the equally weighted hedge fund illiquidity index as predictor. The cumulative differences are averaged across all assets.

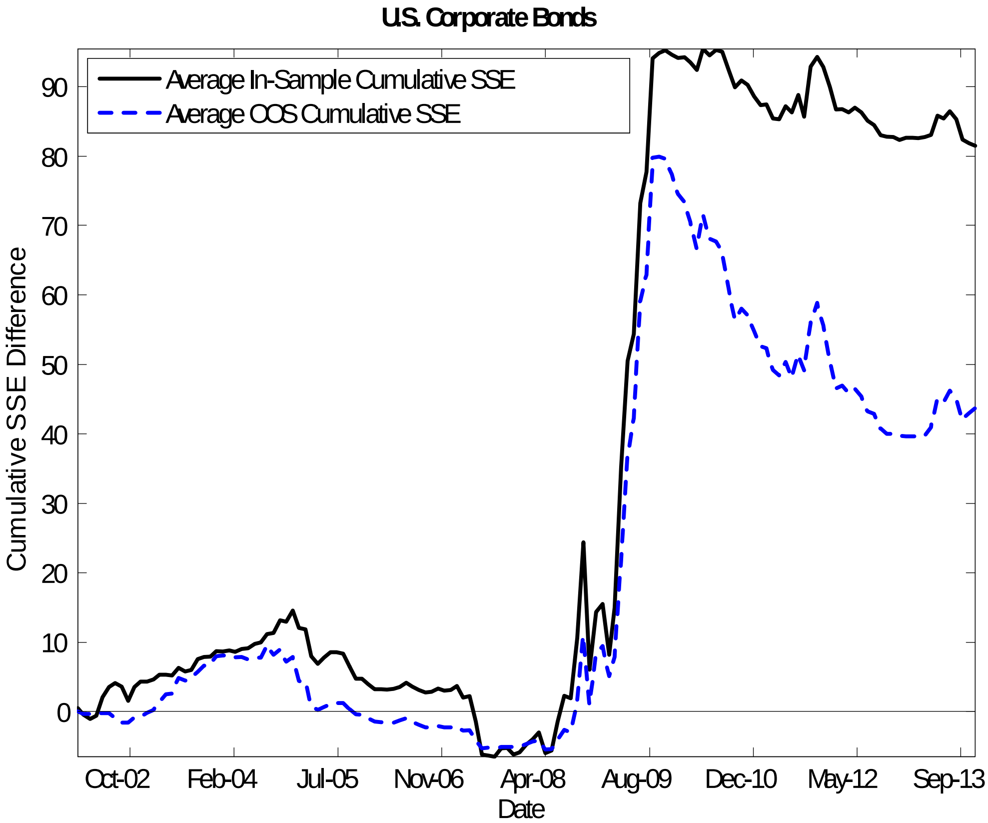

Figure IA.IV: The OOS line shows the difference of the cumulative OOS squared forecasting errors of the historical average model and the single variable model with the equally weighted hedge fund illiquidity index as predictor. Five year rolling windows are used. The in-sample line shows the difference of the cumulative sum of squared residuals of a model with just a constant and the residuals of a single variable model with the equally weighted hedge fund illiquidity index as predictor. The cumulative differences are averaged across all assets.

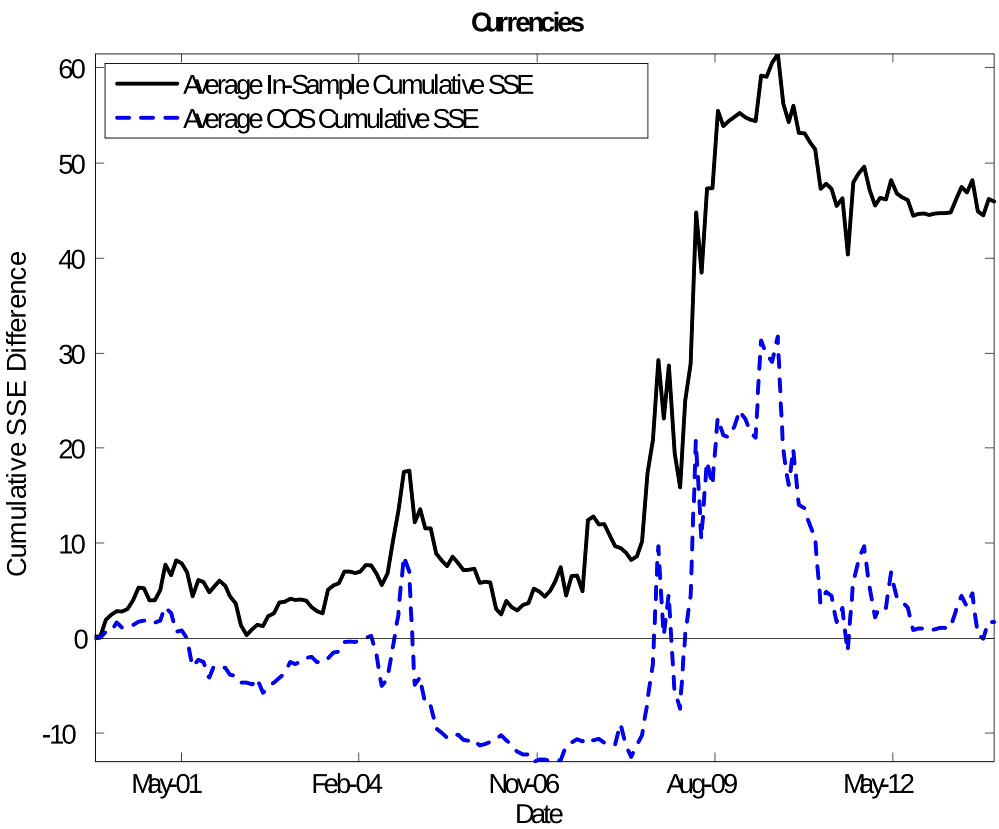

Figure IA.V: The OOS line shows the difference of the cumulative OOS squared forecasting errors of the historical average model and the single variable model with the equally weighted hedge fund illiquidity index as predictor. Five year rolling windows are used. The in-sample line shows the difference of the cumulative sum of squared residuals of a model with just a constant and the residuals of a single variable model with the equally weighted hedge fund illiquidity index as predictor. The cumulative differences are averaged across all assets.

Tabel AI.III: In-Sample Predictive Performance of US Corporate Bonds

Reported are the signs of the predictors (in the case of multiple predictors, it stands for the sign of the hedge fund illiquidity index), the adjusted R^2 of the in-sample predictive regression in %, and the significance of the hedge fund illiquidity index (* for 10% and ** for 5%). The AUM weighted flows are computed over a 12 month rolling window. The time series starts in January 1997 and ends in December 2013. Newey-West standard errors are used.

Panel A: Single Predictor						
Portfolios	**Hedge Fund Illiq. Index**	**Lagged Returns**	**Pastor-Stamb. Traded Liq. Factor**	**VIX AR(2) Shocks**	**VWM Excess Return**	**Hedge Fund Flows**
AAA1-3Y	(+) -0.46	(+) 1.26**	(-) -0.25	(+) 4.28**	(-) 5.00**	(+) -0.45
AAA3-5Y	(+) -0.29	(+) 0.24	(-) 0.08	(+) 4.27**	(-) 5.07**	(+) -0.47
AAA5-7Y	(+) -0.43	(+) -0.17	(-) -0.39	(+) 3.83**	(-) 5.65**	(+) -0.39
AAA7-10Y	(+) -0.23	(+) 0.03	(-) 0.01	(+) 4.53**	(-) 3.84**	(+) -0.37
AAA10-15Y	(+) -0.30	(-) -0.44	(-) -0.10	(+) 4.93*	(-) 4.76**	(+) -0.15
AAA15+Y	(+) -0.09	(+) -0.37	(-) 1.19*	(+) 6.51*	(-) 2.59**	(+) -0.03
AA1-3Y	(+) 1.34	(+) 1.55**	(-) 1.29	(+) 1.11**	(-) 0.43	(-) -0.46
AA3-5Y	(+) 1.44	(+) 0.77*	(-) 1.43*	(+) 1.88**	(-) 1.27**	(-) -0.48
AA5-7Y	(+) 1.19	(+) 0.13	(-) 0.64	(+) 0.73	(-) 0.83	(+) -0.49
AA7-10Y	(+) 1.66*	(+) 0.80**	(-) 1.33**	(+) 3.54**	(-) 1.87**	(+) -0.47
AA10-15Y	(+) 0.11	(+) -0.48	(-) -0.21	(+) 1.92	(-) 1.06**	(+) -0.43
AA15+Y	(+) 1.80**	(+) -0.50	(-) 2.65**	(+) 2.75	(-) 0.44	(+) -0.48
A1-3Y	(+) 4.27*	(+) 7.72**	(-) 0.99	(+) -0.12	(+) -0.44	(-) -0.24
A3-5Y	(+) 2.91*	(+) 2.78**	(-) 1.08	(+) -0.15	(-) -0.42	(-) -0.32
A5-7Y	(+) 3.91**	(+) 2.74**	(-) 1.09*	(+) 0.18	(-) -0.22	(-) -0.11
A7-10Y	(+) 3.25**	(+) 2.29**	(-) 1.51*	(+) 0.33	(-) -0.30	(-) -0.48
A10-15Y	(+) 2.63**	(+) 0.50	(-) 0.32	(+) -0.35	(-) -0.12	(-) -0.50
A15+Y	(+) 3.58**	(+) 0.29	(-) 2.26**	(+) 1.04	(-) -0.42	(+) -0.49
BBB1-3Y	(+) 7.88**	(+) 9.04**	(-) 0.30	(-) 0.02	(+) 1.78	(-) 1.41
BBB3-5Y	(+) 5.80**	(+) 6.37**	(-) 0.15	(-) 0.24	(+) 0.41	(-) 0.90
BBB5-7Y	(+) 6.22**	(+) 6.04**	(-) 0.24	(-) 0.14	(+) 0.40	(-) 0.61
BBB7-10Y	(+) 5.75**	(+) 3.21**	(-) 0.22	(-) -0.31	(+) -0.05	(-) 0.03
BBB10-15Y	(+) 4.92**	(+) 1.65*	(-) -0.04	(+) -0.49	(+) -0.45	(-) -0.22
BBB15+Y	(+) 5.65**	(+) 0.96	(-) 1.54**	(+) -0.37	(+) -0.27	(-) -0.34

Panel A (Continued): Single Predictor						
Port.	**Hedge Fund Illiq. Index**	**Lagged Returns**	**Pastor-Stamb. Traded Liq. Factor**	**VIX AR(2) Shocks**	**VWM Excess Return**	**Hedge Fund Flows**
BB1-3Y	(+) 4.80**	(+) 10.14**	(-) -0.01	(-) 0.63	(+) 2.35**	(-) 0.72
BB3-5Y	(+) 5.08**	(+) 8.39**	(-) 0.36	(-) 1.49	(+) 3.33**	(-) 0.65
BB5-7Y	(+) 5.86**	(+) 8.24**	(-) -0.06	(-) 1.04	(+) 2.74**	(-) 0.31
BB7-10Y	(+) 6.13**	(+) 6.41**	(-) 0.39	(-) 0.68	(+) 2.09**	(-) 0.18
BB10-15Y	(+) 2.99**	(+) 4.27**	(-) -0.04	(-) 2.52	(+) 4.11**	(-) -0.25
BB15+Y	(+) 5.85**	(+) 12.06**	(-) 0.39	(-) 3.59	(+) 6.42**	(-) 0.36
B1-3Y	(+) 3.27**	(-) -0.29	(-) -0.46	(-) 1.99	(+) 5.07**	(-) 0.45
B3-5Y	(+) 5.48**	(+) 14.59**	(-) -0.16	(-) 6.47**	(+) 12.06**	(-) 0.30
B5-7Y	(+) 3.74**	(+) 6.46**	(-) 0.43	(-) 6.31**	(+) 9.59**	(-) 0.21
B7-10Y	(+) 5.11**	(+) 6.82**	(-) 0.96	(-) 3.45	(+) 6.77*	(-) 0.00
B10-15Y	(+) 7.06**	(+) 1.81	(-) 1.18	(-) 0.54*	(+) 4.80**	(-) 0.18
B15+Y	(+) 7.39**	(+) 1.84	(-) 0.68	(-) 3.19*	(+) 5.64**	(-) 0.23
C1-3Y	(+) 2.25**	(+) 0.41	(-) 0.02	(-) 1.32	(+) 4.41**	(-) -0.35
C3-5Y	(+) 7.40**	(+) 12.45**	(-) -0.33	(-) 6.22**	(+) 11.83**	(-) 0.83
C5-7Y	(+) 6.91**	(+) 16.66**	(-) 0.05	(-) 9.86**	(+) 14.12**	(-) 1.28
C7-10Y	(+) 6.24**	(+) 8.38**	(-) 0.77	(-) 3.69**	(+) 10.35**	(-) 1.50
C10-15Y	(+) 1.31	(+) 18.16**	(-) -0.25	(-) 9.18**	(+) 10.33**	(-) -0.16
C15+Y	(+) 5.17**	(+) 6.18**	(-) -0.37	(-) 2.77**	(+) 9.18**	(-) 1.93

Panel B: Multiple Predictors		
Portfolios	Excl. Hedge Fund Illiq. Index	Incl. Hedge Fund Illiq. Index
AAA1-3Y	4.522	(+) 4.049
AAA3-5Y	4.317	(+) 3.976
AAA5-7Y	4.365	(+) 3.953
AAA7-10Y	3.722	(+) 3.421
AAA10-15Y	4.695	(+) 4.413
AAA15+Y	5.634	(+) 5.429
AA1-3Y	2.453	(+) 3.183
AA3-5Y	2.491	(+) 3.382
AA5-7Y	0.459	(+) 1.461
AA7-10Y	4.058	(+) 5.087
AA10-15Y	0.289	(+) 0.359
AA15+Y	2.822	(+) 4.286**
A1-3Y	9.499	(+) 11.348**
A3-5Y	3.256	(+) 5.042*
A5-7Y	3.547	(+) 5.845**
A7-10Y	3.412	(+) 5.392**
A10-15Y	-0.333	(+) 1.998**
A15+Y	2.468	(+) 4.940**
BBB1-3Y	10.975	(+) 15.107**
BBB3-5Y	6.670	(+) 10.305**
BBB5-7Y	6.132	(+) 10.090**
BBB7-10Y	2.752	(+) 6.823**
BBB10-15Y	0.649	(+) 4.312**
BBB15+Y	2.025	(+) 6.010**
BB1-3Y	12.138	(+) 14.807**
BB3-5Y	10.756	(+) 14.169**
BB5-7Y	9.892	(+) 13.606**
BB7-10Y	8.227	(+) 12.273**
BB10-15Y	5.818	(+) 8.282**
BB15+Y	14.763	(+) 18.148**
B1-3Y	6.939	(+) 11.194**
B3-5Y	18.278	(+) 21.704**
B5-7Y	11.810	(+) 15.190**
B7-10Y	10.935	(+) 14.746**
B10-15Y	6.323	(+) 11.941**
B15+Y	6.834	(+) 13.909**
C1-3Y	3.485	(+) 5.592**
C3-5Y	15.928	(+) 21.047**
C5-7Y	21.677	(+) 26.252**
C7-10Y	14.004	(+) 18.198**
C10-15Y	19.661	(+) 20.727**
C15+Y	10.431	(+) 14.136**